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Managing volatile markets: A dynamic capability approach to analytics-driven performance in fast-moving supply chains for sustainable development

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ABSTRACT

The fast-moving consumer goods (FMCG) sector is facing several challenges due to rapid changes in consumer preferences, regulatory pressures, fluctuating resource availability, and complex supply chain operations. Firms are required to integrate data-driven insights into their decision-making processes to develop dynamic capabilities, which help the firms to sense changing market trends and become responsive to market demand by reconfiguring their resources. The main objective of this research is to empirically validate the effect of analytics capability and dynamic capability on firm performance. The theoretical foundation of this research is based on the dynamic capability view. A survey is conducted through a structured questionnaire, and 416 responses are collected from SC managers working in different firms within the FMCG sector in Pakistan. Hypotheses are validated using partial least squares structural equation modelling. The model is further validated, and the contribution of each input feature is measured by using a machine learning model, “Support vector regressor (SVR)”. This research adds to the current literature on sustainable supply chains by empirically testing how analytics capability, when integrated into dynamic capabilities, which include agility, visibility, and adaptability, allows companies, particularly in the FMCG industry, to react proactively to environmental and market dynamics, thus supporting SDGs like responsible consumption and production and sustainable communities.

1. Introduction

The manufacturing sector is under unprecedented strain due to rapid globalization, which makes it necessary for organizations to stay up-to-date with technical breakthroughs and effectively adapt to shifting customer needs [1]. Previous research indicates that this can only be accomplished by utilizing skills like agility, visibility, adaptability, and transparency [2,3]. Supply chains (SCs) that are agile enough to react quickly to short-term shifts in demand and adaptable enough to restructure themselves in response to longer-term shifts in the market are essential for successful businesses. The ability of a firm to adapt to changes in the market, such as variations in demand patterns in terms of quantity, quality, and variety, as well as supply patterns in terms of disruptions and shortages, is known as supply chain (SC) agility [4]. The ability of the organization to implement SC design modifications in response to long-term opportunities is known as SC adaptability [5]. SC visibility, agility, and adaptability are collectively called dynamic capabilities (DCs) since they are created and renewed in response to shifts in consumer demand.

Data is essentially required for creating value, enabling SC to enhance visibility and build dynamic capability in a highly volatile business environment [6,7]. SC visibility is an important part of supply chain management (SCM), which includes collecting, evaluating, and sharing information in different stages of SC. Managers collect and evaluate information from a variety of SC participants, including vendors, customers, wholesalers, and retailers, regarding the movement of goods, services, and information [8]. The use of big data analytics, machine learning, and artificial intelligence technologies as essential tools for SC data analysis has gained significant traction in recent years for SC decision-making and problem-solving [9]. The field of supply

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chain analytics (SCA) is a recent development that is gaining maturity. It has also emerged as a valuable competitive resource for enhancing SCM performance overall and business performance to meet consumer expectations [10]. Supply chain analytics capability (SCAC) acts as an analytical tool for SC-related problems, and demonstrates how normative, descriptive, and predictive technologies are applied to SC planning, procurement, production, and delivery operations. SCAC is the degree to which SC participants engage and communicate with one another, with an emphasis on data analysis [11]. According to [12], SCAC is an integrated analytical approach that offers strong insights into managerial, technological, and personnel skills, including compatibility, control, connectivity, and planning, for business decisions.

Unstable markets and decentralized and complex SC operations can all threaten the stability of SCs and increase their susceptibility to risks and disruptions [13]. Prior studies have demonstrated that analytics capability (AC) has a favourable impact on business performance and the operational transparency of the SC, highlighting important part that relational qualities play as mediators or moderators [11,12,14] used a technological, organizational, and environmental framework to find different determinants that affect the adoption of AC and its impact on competitive performance of the firms. The capacity to use analytics effectively has been shown to be more strongly correlated with operational performance in SC for organizations that also possess the organizational flexibility required to move quickly and efficiently on the insights provided by analytics [15]. The use of AC to improve SC transparency through positive effects on sourcing, producing, and delivering is validated by [16]. Suppliers may find it helpful to adapt and utilize AC to maximize the value of their SC relationships [11]. AC can improve a company's operational efficiency and offer insights and trends that could support innovative supply chain operations [17,18]. The importance of intangible SC capabilities, such as organizational learning and a data-driven culture within the SC, was highlighted by [19], who underscored that these capabilities are difficult to replicate than those abilities which are tangible, like human resources. All the previous studies have validated the impact of AC or DC on performance separately, but there is a lack of empirical evidence on how these two capabilities collectively affect the firm's performance, specifically in fast-moving consumer goods (FMCG) sector. So, based on this study gap, the research question of the research is

RQ: How do analytics capability and dynamic capability affect the firm performance, and what will be the mediating effect of dynamic capability between analytics capability and firm performance in the FMCG sector?

There is a very significant contribution of the research because it connects AC, which is a technologically enabled capability, to DC, which is a human-centric capability. The research shows that AC is not only about collecting and analysing the data, but it also forms a strategic asset of firms, which is called agility, which is the capacity of a firm to adjust itself according to volatile market situations, which plays a pivotal role in FMCG, which is a very fast-paced sector. The research is different from previous research because it provides the insight that AC alone is not sufficient to improve performance, but it is its integration with the DC of the firm that brings tangible improvement in output. In fast-moving industries, the data from customer feedback and social media always has an effect on strategic decisions, so DC becomes a very important capability because it translates the raw data into actionable strategies. The research is sector-specific, which provides unique insights for FMCG as this is an area that has its own challenges, such as very tight SC, rapidly changing consumer preferences, and high turnover, as well as it is traditionally a less digitalized field. In previous research, some studies have validated the effect of AC on performance, but for this study, DC is taken as a mediating factor, which is the novelty aspect of this research. The measurement of AC and DC through structured variables provides a granular understanding of how AC, which not only includes managerial and technical aspects but also focuses on data-driven culture, helps the DC, which encompasses visibility, agility, and adaptability to rapidly sense the trends of market, to adapt to the changes, and sustain the flexible organizational structure. The distinct dynamics of SCs in developing countries, such as Pakistan, necessitate careful consideration, and this study's approach is purposefully designed to reveal nuances that might have gone unnoticed or understudied. Building upon these motivations, this study is guided by the following research objectives:

1. To examine the impact of analytics capability on dynamic capabilities (visibility, agility, and adaptability) in the FMCG supply chain context.
2. To investigate the mediating role of dynamic capabilities between analytics capability and firm performance.

The novelty of this study also lies in its methodology, in which different machine learning models are used, and the best-performing model, called support vector regressor (SVR), is selected for further validation and to find the most important input feature contributing to improving the firm's performance. This study is grounded in the Dynamic Capability Theory [20], which posits that companies must develop higher-order capabilities to respond, combine, and reconstruct internal and external resources in environments characterized by accelerated change. This model adds to this theory by empirically proving how analytics capability supports companies in building and upgrading dynamic capabilities through which they achieve enhanced performance outcomes. Current study contributes to the dynamic capabilities literature by situating it within the FMCG, which experiences greater volatility and sustainability pressure. FMCG sector globally and in developing countries like Pakistan is facing several sustainability challenges that include high use of energy and water in manufacturing, plastic waste from packaging, industrial waste due to inefficient production, and inadequate supply chains, which cause spoilage and emissions. These aspects point toward the immediate requirement for data-driven approaches to promote SC responsiveness and sustainability.

2. Literature review

2.1. Dynamic capability view

The dynamic capacity view (DCV) emphasizes the significance of constantly modifying a firm's resources, processes, and procedures in response to shifts in the market, technological advancements, and consumer needs [20,21]. Developing, expanding, and adapting complementary resources can help a company improve its dynamic capabilities so it can better serve customers and maintain a competitive edge [22,23]. To improve the positive outcomes, a company must modify its own resources or operational procedures, make effective use of outside resources, or seize opportunities [24]. For instance, to improve performance, organizations need to manage risks, reconfigure (combine, learn, integrate, and cooperate) resources, revive environmental sensitivity, and take advantage of market opportunities [25]. Reviving environmental sensitivity entails that a company should be conscious of or promote knowledge bases about global competition, unique customer needs, cutting-edge technologies, and the tactics and practices of top suppliers, competitors, and customers in challenging circumstances. An organization must plan, acquire, execute, and modify technological knowledge within its organizational frameworks once it seizes new resources, opportunities, and technological developments from cooperating partners [26]. In the meantime, they must evaluate their new and current capabilities to rebuild or design their technologies so that they meet market demands [27].

The model presented in this research can be well explained through DCV, as AC uses data, technology, and tools to improve SC operations.

These assets are very important for firms to quickly respond to the changing markets and improve efficiency. The capacity of any organization to use the SC data to make informed decisions is an important capability that helps organizations to improve customer service and to optimize the SC processes. DC enables the firms to identify the threats and available opportunities in the market, and AC can strengthen their ability to find emerging trends, new market developments, and seize all the prevailing opportunities through quickly adapting their SCs. DC encourages firms to transform their existing resources to create new value, and AC helps to locate new areas for improvements in inventory, suppliers' relationships, or logistics. Companies can then utilize this data to adjust their SCs by making technological investments, changing their operations, or forming strategic partnerships.

2.2. Analytics capability (AC)

Businesses make a wide range of decisions at various levels, ranging from tactical choices with long-term effects to daily operating decisions. For all these decisions to be made, fast and efficient data collection and analysis are necessary. The past decade has witnessed a massive rise in the amount of data that businesses collect and analyse, made possible by developments in information technology and electronic systems [28,29]. For companies, there are a plethora of opportunities and challenges because of the extraordinary rise in the affordability of data collection and analysis. Businesses that can successfully integrate and use data from both inside and outside the company have a competitive edge. Such capacity building necessitates a large financial outlay. The literature has evidence that enhancing analytics skills for data use effectively leads to better operational and strategic decision-making, which enhances corporate performance [10,11].

Typically, three widely acknowledged foundational big data resources are utilized. These consist of material resources (like spending money on big data analytics technology), immaterial resources (like organizational learning and the creation of a data-driven cultural competence), and human resources (like management and the development of technical capability). The emphasis on SCM problems that frequently cut across firm borders is the primary distinction in the literature between SCAC and the generic analytics capacity [18]. Based on existing literature, SCAC refers to a firm's capacity to process data to better understand the SC, make better SC decisions, identify risks resulting from changes in the business environment, and choose the best course of action in a variety of business scenarios [11]. Managers use descriptive analytics to comprehend the SCs, which include information on facilities, inventory, and demand, and they then use this knowledge to build models not only for firms but also for upstream and downstream partners. This serves as the foundation for increasingly intricate research and necessitates data-sharing agreements with SC partners. Prescriptive analytics helps SC decision-making by identifying the optimal course of action using simulations or optimization models. The final section of SCAC deals with forecasting, risk assessment, and the effects of potential future variations to the business environment, like changes in supply or demand.

2.3. Dynamic capability (DC)

The organization's "sense and then seize new opportunities, and to reconfigure and maintain knowledge assets with an objective of achieving a sustained competitive advantage" is what is referred to as its dynamic capabilities. SC operations must be managed and optimized, which requires SC visibility [30]. It entails working with external partners and exchanging data with the SC network to obtain up-to-date knowledge about production schedules, inventory levels, and transportation conditions [15,31]. SC visibility helps companies reduce risks, save costs, and improve customer satisfaction by anticipating disruptions and taking action swiftly [32]. SC agility is positioned as a dynamic skill to seize since it allows an organization to quickly identify opportunities and threats in the marketplace [33]. Agility includes organizational structures, procedures, mindsets, and information systems, and is characterized by flexibility and responsiveness. The concept of supply chain agility highlights the ability to adapt and change within the specific structural design of the SC. SC adaptability is considered a transformative DC because the SC structure and resource base change over time in response to market developments [5]. Visibility, adaptability, and agility integrate, and a complex structure can be developed that can immediately detect the prevailing changes in the market [34].

The organization's DC shows how well it can adjust its unique resources according to fluctuating and dynamic environmental conditions. Firms with strong DC are more proactive, and they can anticipate and mitigate the prevailing risks in their SCs in a better way. Due to their proactiveness, they can deploy better strategies in case of natural disasters or geopolitical risks. In case of a sudden disruption, such as COVID-19, they can reconfigure their resources and find alternate supplies to maintain their operations. Similarly, dynamic capable companies are more flexible in their structure to adapt to emerging technologies. If organizations are capable of reconfiguring their resources according to quickly changing circumstances, then they will gain a competitive edge that will be difficult for their competitors to replicate. This resource will help them to consciously improve, evolve, and keep them ahead of their competitors.

2.4. Analytics capability, dynamic capability, and sustainable development

Firms that are operating in a highly volatile environment in today's business are facing high pressure from regulatory bodies, global sustainability standards, and different stakeholders to implement sustainable business practices [35]. Analytics capabilities of any firm can help to improve the sustainability indicators through accurate forecasting, reduction of industrial waste by improved efficiencies, and proactively addressing environmental and social concerns [6,7]. Similarly, DC, including visibility, adaptability, and agility, can help organizations to quickly adjust their operations according to expectations of society, pressure from regulatory bodies, and different challenges in environment, which can bring better results [8]. Therefore, integrating analytics with dynamic capabilities allows for a more thorough and proactive approach to sustainable growth by immediately integrating sustainability considerations into supply chain strategic and operational decision-making processes [36].

2.5. Literature gap and contextual novelty

Although there are various studies that have investigated the relationships among AC, DC, and firm performance [37,38], but most studies lean towards generalization without considering industry-specific contexts. There is a wide range of existing literature that focuses on generalized manufacturing contexts or specific industrial sectors such as automotive, electronics, and healthcare [8,10] but there is a significant knowledge gap regarding the specific implications within high-velocity, consumer-oriented industries such as FMCG. The FMCG sector has various attributes of rapid changes as per the requirements of the customers, rapid product life cycles, a high rate of turnover, and intense competition. These characteristics necessitate that firms in this sector ought to respond quickly to market forces and employ AC more aggressively than firms in typical manufacturing industries [11]. Moreover, many studies in the literature have also considered the AC or DC in isolation, in which a few studies have explored how these two capabilities act in high-volatility situations. In FMCG sector, volatility is not considered only about the fluctuation in demand but also about regulatory shocks (e.g., new packaging waste directives) and social pressures (e.g., consumer demand for ethical sourcing). Despite the pivotal contribution that analytics and DC can make to volatility management in FMCG, empirical research on how these capabilities collectively affect firm performance in this regard is scarce. There is a vast knowledge gap in literature regarding the combined interactions between data analytics and DC within FMCG supply chains, with implications for firms' responsiveness and performance in extremely volatile market environments. These factors all amplify the imperative to comprehend how companies create dynamic reactions out of analytics-driven insights. The current research fills this relatively unexplored intersection, thereby contributing both to the theoretical debate on dynamic capability view (DCV) and to practice by highlighting a pressing managerial gap: how analytics is transformed into sustained adaptability in high-velocity consumer markets in a developing country context with unique contributions to knowledge in form of sector-specific insights.

3. Hypotheses development

3.1. Analytics capability (AC), dynamic capability (DC) and firm performance

This study uses DCV and makes an important advancement in that AC can help firms efficiently collect, organize, and analyse large amounts of data inside intricate SC networks. Through rigorous data analysis and predictive modelling, AC can provide firms with improved DC through more precise and reliable information [9,39]. Firms with AC are more likely to create cross-functional teams or workshops with an emphasis on data analytics to gain a deeper understanding of the people that make up their SC, including customers [19]. Strong AC skills enable businesses to quickly evaluate massive datasets, extract important data, and obtain crucial insights by leveraging cutting-edge technology and techniques [40]. By leveraging its consumer data, a business may forecast changes in the market and decide when to launch new items to satisfy evolving consumer needs [41].

Because SCs deal with a variety of risk factors, it becomes necessary to monitor and maintain the quality of data to effectively predict upcoming trends. These are effective steps to ensure DC because disruptions could occur if SCs encounter hitherto unseen worldwide uncertainties brought on by external factors like climate change and pandemics [19]. These disruptions will cause the commodities in the SC to either arrive late or not at all, which will reduce the agility of SC. Instead of depending just on intuition, organizations with good SC risk assessments make data-driven decisions about their SCs [10]. Strong SCAC enables organizations to analyse SC data, get information from suppliers in real-time, keep an eye on supply chain activity, and anticipate possible disruptions [42]. By utilizing this data, businesses can quickly create efficient backup plans that deal with possible hazards and improve dynamic capability [37]. Therefore, for this research, first two proposed hypotheses are

H1: AC has a positive effect on dynamic capability.
H2: AC has a positive effect on firm performance.

3.2. Dynamic capability and firm performance

The concepts of SC agility, visibility, and adaptability are dynamic skills that have the power to influence performance. They make it easier to reallocate resources, detect and take advantage of changes in the environment, as well as opportunities and risks. Through SC agility and adaptability, dynamic capabilities, which are sources of competitive advantage that are difficult to replicate, can boost company performance [43]. Enterprises cultivate SC flexibility and agility to get a competitive edge. They establish capacities to utilize and reorganize SC assets to address fluctuations in both supply and demand, and market and economic configurations [5]. There are several ways in which DC can improve cost performance. It makes it possible for businesses to deal with SC disruptions smoothly and economically, a significant expense element for global SCs. By improving supply and demand synchronization, SC agility helps businesses cut expenses associated with inventory and transportation. Delays can lead to lower cost of production, shipping, and inventory by resulting in fewer stock, increasing variants, and volume-based economies of scale. Faster manufacturing process modifications, reduced material and service replacement periods, increased throughput, and set-up times allow businesses to customize goods affordably without having to resort to product markdowns brought on by excess inventory.

Operational performance can also be positively impacted by DC. It helps businesses to guarantee the accuracy of a service and to meet deadlines for delivery [44,45]. Quick and adaptable production process modifications, flexible inventory relocation, and short material and service replacement times reduce lead times and improve customer delivery management. Product quality may benefit from the capacity of a firm to go through incremental design modifications and change technical requirements quickly, to eliminate various sorts of waste, and to effectively respond to quality problems [46,47]. Agile and flexible SCs have an impact on delivery and service level performance because of their ability to recover fast from shocks outside the system [48]. By attaining structural flexibility via diverse manufacturing and sourcing footprints, companies can enhance their performance in terms of delivery and service level. Being inventive fosters shorter design cycles and lead times, and adaptable design skills, all of which are beneficial for timely product launches and market entry. Each of these justifications leads to the hypotheses given below:

H3: Dynamic capability has a positive effect on firm performance
H4: Dynamic capability mediates the relationship between AC and firm performance.

3.3. Research model and construct operationalization

The conceptual framework of this research is grounded in DCV. Independent variable AC is measured through four constructs comprising managerial competency, human resource expertise, analytics-driven culture, and technical capability of the organization. Similarly, DC is measured through visibility, adaptability, and agility. Direct effect of AC will be validated on DC and firm performance (H1 and H2). A direct effect of DC will be measured on firm performance (H3), and an indirect effect (mediating effect) of DC will be observed between AC and firm performance (H4) as shown in Fig. 1. All the variables are selected from the extensive literature review, and their detail is provided in Appendix A. All the variables, i.e., AC, firm performance, and DC, are considered as reflective constructs.

4. Research design

Based on the previous literature, conceptual framework, and feedback from experts (Academicians and SC professionals) a questionnaire was developed to collect the data from relevant professionals. Responses were gathered using a five-point Likert scale, with options ranging from 'strongly agree' (1) to 'strongly disagree' (5). A pilot survey was employed initially by a group of SC managers to improve the clarity and reliability of the survey. The feedback from the experts was incorporated to improve the wording, remove any ambiguity, and increase the relevance of the survey. The feedback was iteratively incorporated that resulted in a refined final questionnaire that was used to collect the data from respondents. The data was collected from a developing country (Pakistan) in the South Asian region. Data was collected from the sector "Fast-moving consumer goods". Consumer goods are commodities that are intended for frequent individual consumption. They offer a wide range of products in both food and non-food sectors. Additional classifications for them include slow-moving consumer goods (SMCG) and fast-moving consumer goods (FMCG). The definitions are predicated on the frequency of product sales to customers, which is a determining factor in the goods rotation process. The useful life of FMCG is less than 1

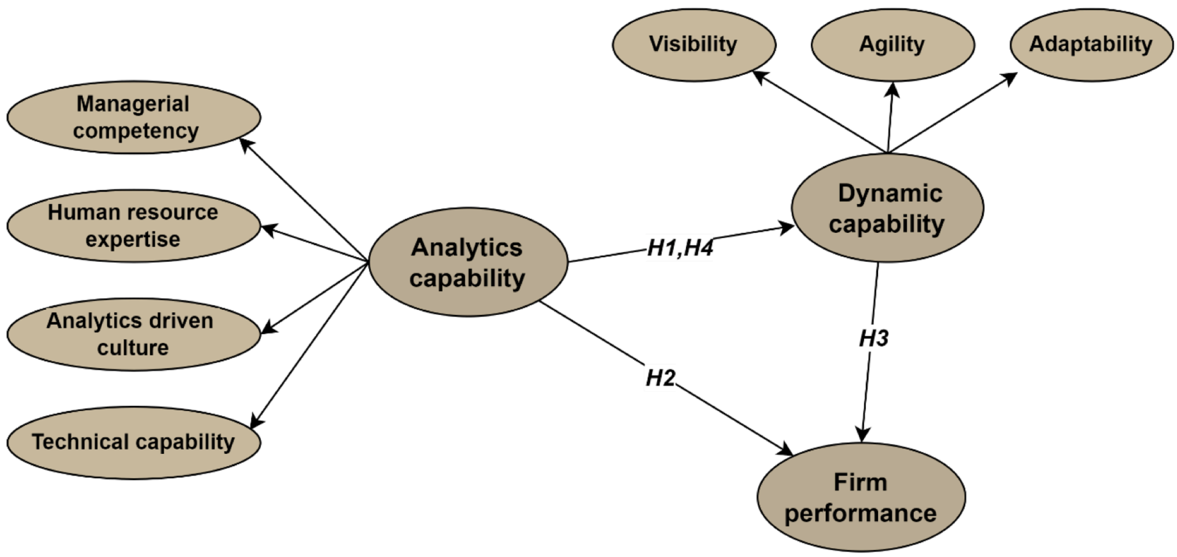

Fig. 1. Theoretical Framework.

year, and consumers must spend on them frequently. Its examples include food and beverages, apparel and footwear, personal care, tobacco, and cleaning products. The SMCG has a useful life of less than 1 year. Their examples are furniture, home appliances, etc. Their sale frequency is lower and is not rotating as quickly as FMCG. This industry plays a vital role in Pakistan's economy. The retail sector has been the major contributor to country's GDP for last few years.

4.1. Data collection

For data collection, the questionnaire was distributed among the managers who are involved in tasks such as warehousing, production, procurement, inventory, and logistics [49]. The information regarding these professionals was collected using different platforms. One source of information was B2B databases, which provided information regarding SC managers working in various firms of FMCG sector in Pakistan. In addition, data of professionals was obtained from Quality and Productivity Society of Pakistan as well as from chamber of commerce of different cities. Another major source was LinkedIn, which is a platform where contact details of different professionals are available regionally. A final sample of 2180 SC managers was finalized, and an email was sent with a request to fill survey. The researchers also visited the different firms in Pakistan to gather the data. The second and third reminders were sent to all the managers with a request to respond at their earliest convenience. They were informed about the importance of their participation in survey for the reliability and accuracy of results. After these efforts, a total of 457 completed questionnaires were received during a time October 2023 and August 2024. A 21 % response rate is satisfactory according to the previously conducted empirical studies from SC managers [50,51]. The anonymity of all the respondents is ensured to get unbiased responses and to maintain the ethical aspects for safeguarding the confidentiality of the participants. The key informant method was used in scrutiny process, and all the responses from participants were deleted whose job titles had no relevance to SC operations. Similarly, surveys with missing information were discarded. A total of 416 responses made up the final dataset. A priori power analysis using G*Power 3.1 was conducted to confirm the adequacy of the sample size. Based on calculations on a medium effect size ($f^2 = 0.15$), 0.05 significance level, 0.90 statistical power, and seven predictors, the suggested minimum sample size is about 153. The sample of 416, therefore, ensures sufficient statistical power and enhances the reliability of the findings [50,52]. The sampling method was purposive in targeting supply chain and operations professionals working in the FMCG. This targeted method maximizes the applicability of the information to the research purpose, so that the findings established are grounded in the practical realities of the sector under investigation. The important point to note is that all the surveys are collected only from medium and large firms. For this research, the size of the firms is based on number of employees. The firms with fewer than 50 employees are considered smaller firms. Firms with employees more than 250 are categorized as large firms. Organizations having employees between 50 and 250 are considered as medium size organizations. Smaller firms were not considered in data collection process. One more important point is that minimum required experience of respondents considered for this research is 3 years. Some responses from young professionals are not included in final dataset.

A non-response bias test is conducted to improve the quality and fairness of research findings. It is conducted to ensure that dataset represents the targeted population. For this purpose, 120 responses received at the start of data collection were compared with the 120 responses collected at the end of data collection phase using a paired *t*-test using guidelines of [53]. The results show no significant difference between both groups which validate that non-response bias does not exist.

4.2. Common method bias (CMB)

CMB can occur in survey-based collected data, and some indicators may show similar variations due to this problem. Scholars have used different techniques to deal with this problem [54]. First, the data is collected carefully only from relevant professionals who have relevant knowledge of SC. The structure of the survey was very simple, and questions were asked with clarity. Respondents were already informed about the objectives of this research, and they were aware that their identity would not be revealed. Moreover, after the collection of data, post hoc analysis was used to assess the CMB using a one-factor test [55]. For this purpose, eigenvalue unrotated exploratory factor analysis was used, and there were several components with one factor explaining variation of 30.88 %. This shows that problem of CMB does not exist.

Harman's method has received a lot of criticism [56], so another method is used which is based on the use of marker variables [57,58]. Marker variables are those that are not related to any of the variables used in the research. The model of the study without a marker variable is compared to the model that does not use a marker variable. The result shows that there is no significant change in the relationships of variables by the inclusion of marker variables (Appendix B). It can be concluded that CMB is not significant in this research.

5. Data analyses and results

In this research, SmartPLS 4 is used for the data analysis to apply partial least squares structural equation modelling (PLS-SEM) [59]. The main advantage of using this tool is that it can handle large and complex datasets, and it does not assume that given data is normally distributed [60]. This software tool can conduct latest-generation statistical analysis such as to check the reliability of measurement models, testing the significance of path coefficients for hypothesis validation, and examining the model's robustness. It can also check the nonlinearity of model, observe the heterogeneity in the data, and conduct multi-group analysis in observed heterogeneity. It can be used to assess the complex relationships of variables, such as mediation and moderation analysis. Its important attribute is the use of bootstrapping techniques to validate the significance of paths [61]. For this study, analytics capability is measured through four constructs which are further measured through three questions each. Similarly, DC is measured through three variables and each of them is measured through a set of questions. DC is also used as a mediation variable between AC and firm performance.

Another important step is the use of SEMinR package of R, which is used to cross-validate all the results. SEMinR is user-friendly syntax-based tool to handle complex models in which SEM is employed. The results of SEMinR and SmartPLS are cross-checked with each other to increase the reliability of the results.

5.1. Measurement model

The relationship between an indicator and its variable is considered significant if its factor loading is greater than 0.5 [62]. As shown in Table 1, factor loadings of all lower and higher constructs are above the minimum required value. Only loading of one item of visibility (Visi1) was below 0.5, so it was removed. Similarly, to assess the validity of all constructs, Cronbach's alpha and composite reliability (CR) are computed, and all the values are greater than the minimum threshold, i.e., 0.7 [63,64]. The next step is to check the convergent validity of all the constructs. The value of the average variance extracted should be more than 0.5 [65]. It has been shown that all the values exceed the threshold value. So, convergent validity is established for all the lower and higher-order variables.

Discriminant validity is assessed using two techniques. First is Fornell–Larcker criteria, according to which the correlation of construct should be less than its $\sqrt{AVE}$[66]. Another technique is the heterotrait–monotrait (HTMT) ratio, which should be less than 0.9 [67]. Table 2 shows that all the criteria are satisfied, which establishes the discriminant validity. In this table, bold and italicized values in a diagonal row are $\sqrt{AVE}$, which are all greater than the values below this diagonal row, which are correlation of constructs. Similarly, the values, which are above these diagonal rows, are HTMT values, which are all less than 0.9. These values satisfy the above-mentioned two criteria, so it can be concluded that discriminant validity is established.

5.2. Structural model

The first step in the structural model analysis is to conduct the multicollinearity test using variance inflation factor (VIF). The VIF ≥ 3.3 is considered significant for multicollinearity [68]. For this research, it is

Table 1
Factor loadings, reliability, and validity.

Constructs	Item	Loadings	(VIF)	Cronbach's alpha	CR (rho_a)	CR (rho_c)	(AVE)
Lower-order constructs							
Technical capability	Tech1	0.810		0.698	0.718	0.832	0.624
	Tech2	0.706					
	Tech3	0.847					
Managerial competency	Manag1	0.792		0.745	0.748	0.855	0.662
	Manag2	0.838					
	Manag3	0.811					
Human resource expertise	Human1	0.854		0.714	0.721	0.839	0.635
	Human2	0.800					
	Human3	0.731					
Analytics-driven culture	Analy1	0.914		0.777	0.793	0.872	0.695
	Analy2	0.753					
	Analy3	0.825					
Visibility	Visi1	Deleted		0.726	0.719	0.845	0.647
	Visi2	0.829					
	Visi3	0.865					
	Visi4	0.709					
Agility	Agil1	0.704		0.771	0.774	0.844	0.521
	Agil2	0.757					
	Agil3	0.738					
	Agil4	0.672					
	Agil5	0.734					
Adaptability	Adap1	0.723		0.716	0.733	0.823	0.538
	Adap2	0.683					
	Adap3	0.723					
	Adap4	0.801					
Firm Performance	Perform1	0.718		0.801	0.840	0.858	0.548
	Perform2	0.758					
	Perform3	0.777					
	Perform4	0.673					
	Perform5	0.771					
Higher order constructs							
Analytics capability	Technical capability	0.738	1.434	0.824	0.827	0.884	0.657
	Managerial competency	0.866	2.159				
	Human resource expertise	0.807	1.814				
	Analytics-driven culture	0.824	1.908				
Dynamics capability	Visibility	0.850	1.732	0.809	0.809	0.887	0.723
	Agility	0.844	1.719				
	Adaptability	0.857	1.848				

Table 2
Fornell–Larcker criterion & HTMT values.

	Technical capability	Managerial competency	Human resource expertise	Analytics-driven culture	Visibility	Agility	Adaptability	Firm performance
Lower-order constructs								
Technical capability	***0.79***	0.71	0.583	0.61	0.593	0.62	0.695	0.365
Managerial competency	0.519	***0.814***	0.841	0.831	0.729	0.711	0.654	0.367
Human resource expertise	0.423	0.619	***0.797***	0.775	0.695	0.597	0.62	0.274
Analytics-driven culture	0.456	0.637	0.583	***0.833***	0.632	0.635	0.611	0.281
Visibility	0.438	0.552	0.525	0.491	**0.804**	0.71	0.815	
Agility	0.46	0.548	0.462	0.505	0.558	**0.722**	0.797	0.336
Adaptability	0.504	0.489	0.456	0.466	0.6	0.596	**0.734**	0.339
Firm performance	0.305	0.304	0.239	0.247	0.308	0.285	0.285	**0.74**

Higher order constructs	Analytics capability	Dynamics capability	Firm performance
Analytics capability	***0.81***	0.875	0.373
Dynamics capability	0.715	***0.85***	0.383
Firm performance	0.339	0.345	***1***

clear in Table 1 that all the values of VIF for all the constructs are less than 3.3. The highest value among all constructs is 2.159 for managerial competency. Similarly, for higher-order constructs, the VIF value of analytics capability with DC and firm performance is 1 and 2.045, respectively, and VIF between DC and firm performance is also 2.045. To assess the quality of the model standardized root, mean square residual (SRMR) is calculated, and its value is found to be 0.067, which is less than the threshold value of 0.08 [69]. Fig. 2 describes the details about the SEM employed here. It not only shows the factor loading values for analytics capability, dynamic capability, and firm performance (arrows pointing from these constructs to their items in yellow) but also shows their significance (p-values in brackets). All the values are significant as determined through bootstrapping procedure. In addition, it also shows the beta coefficient values, which represent the effect of one construct on another. The details of direct and indirect effects are given in Table 3.

It is clear from table that analytics capability has a significant effect on DC (β=0.715, $t = 27.29$), which validates the first hypothesis, second hypothesis is also validated as analytics capability also has a direct significant effect on performance (β=0.189, $t = 2.962$). Third hypothesis was about the effect of DC on firm performance, which is also true as (β=0.209, $t = 3.155$). The last hypothesis is about the mediation effect of DC. The results reveal that there is a significant indirect effect (β=0.15, $t = 3.105$) of analytics capability on firm performance. Its total effect is computed as (β=0.339, $t = 6.953$), which is so far significant after mediator is added (β=0.189, $t = 2.962$). It concludes that DC plays a complementary, partial mediating role between analytics capability and firm performance.

Table 3
Direct and indirect relationships of constructs.

Direct effect			
Hypothesis	Beta Coefficient	T value	Result
H1: Analytics capability -> Dynamic capability	0.715	27.29	Supported
H2: Analytics capability -> Firm performance	0.189	2.962	Supported
H3: Dynamic capability -> Firm performance	0.209	3.155	Supported
Indirect effect			
H4: Analytics capability -> Dynamics capability -> Firm performance	0.15	3.105	Supported

The R^2 value is used to assess the goodness of the model. It shows the variance of dependent variables explained by independent variables. The R^2 value of DC is 0.511, and firm performance is 0.136. The minimum value should be larger than 0.1 [70]. For this research, the R^2 value of DC is substantial but weak for firm performance, according to [71]. Another important parameter is effect size (f^2) value. According to the criteria devised by [52], the effect size of analytics capability is very large (f^2>0.35) but effect size is small for analytics capability (f^2=0.02)

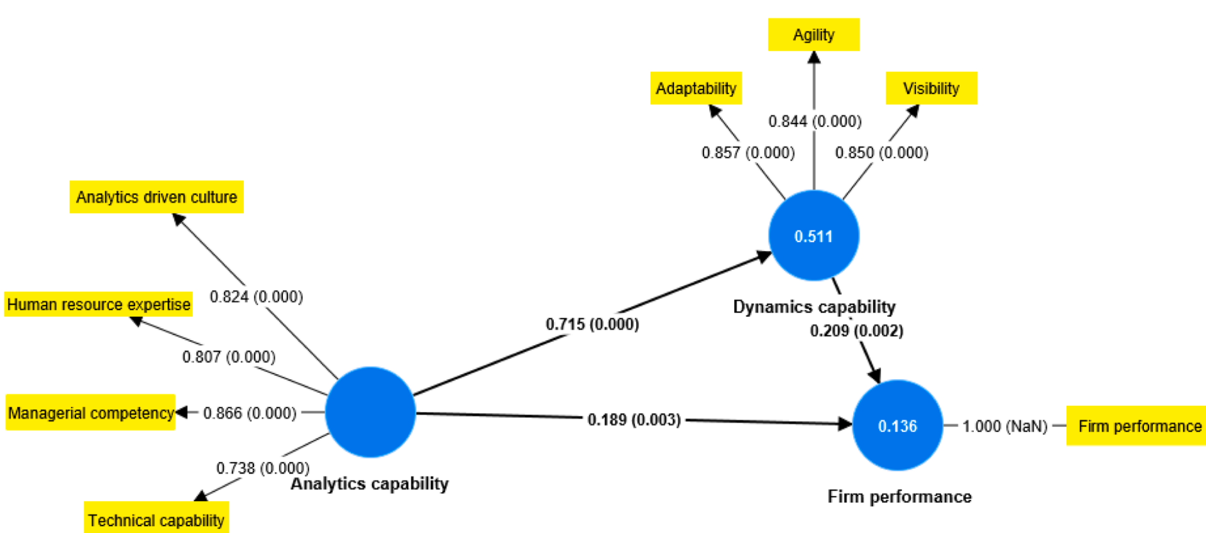

Fig. 2. Structural model.

and DC (f^2=0.025) on firm performance. However, to evaluate the model further in detail, some of the latest generations of statistical tests are performed in this paper.

To check the predictive relevance of model, Stone–Geisser (Q^2) is performed using a blindfolding procedure. If Q^2>0, then model is considered to have predictive relevance [71]. The Q^2 value of both dependent variables, i.e., DC and performance, is 0.506 and 0.111, respectively.

5.3. Evaluating firm performance through SVR model and feature importance analysis

To further validate the results of this study, and to find the importance and contribution of each input feature to improve firm performance, a machine learning algorithm, "support vector regressor (SVR) is used. Different models were used, including "Decision tree, Random forest, KNeighbors, GradientBoosting, and XGBRegressor but the SVR was finally selected due to its better performance metrics. The optimum parameters are selected for SVR through hyperparameter tuning. After this procedure, the best parameters are selected, which include a linear kernel, value of regularization parameter of 0.1. This procedure improves the generalizability of the model, creates a balance between underfitting and overfitting of the model, and provides the best accuracy. The latent variable scores for three constructs of DC and four constructs of AC are used as input data. Data was split into training and testing data with a ratio of 80:20. Its R^2 value is 0.147, which is very close to the value provided by SmartPLS, which validates the previous results. The value of mean square error (MSE) is 0.7952. The model is trained and evaluated. The complete code for this model can be accessed at:

Supplementary code for predicting firm performance using optimized support vector regression

In the next stage, feature importance of the model is evaluated using SVR. Fig. 3 provides a bar graph that shows the importance of input features for firm performance. Agility performs the most critical role, which is followed by managerial competence, technical capability, and visibility. The point to be considered is that all of these features are critical contributing factors, but some of them are more important when compared to others.

SVR is employed as a supplementary method to cross-verify results derived from PLS-SEM and to measure the contribution of single input features. In this regard, while PLS-SEM focuses on examining causal links between latent variables, SVR is a machine learning procedure that assesses the non-linear predictive ability of input variables on firm performance. By comparing SVR's R^2 and MSE with PLS estimates and conducting a feature importance analysis, this research provides a second level of rigor to the findings. This enhances the empirical accuracy of current model by verifying that key constructs, agility and managerial competence, consistently influence performance outcomes.

5.4. PLSpredict

It is used for out-of-sample prediction [72]. This method is used in this research to assess the predictive quality of the model. In its procedure, the model is trained on training data, and it is tested on hold-out data. The first step is to check the distribution of prediction errors. For this purpose, Kolmogorov-Smirnov test is employed, and results show that data is not distributed normally (Appendix C). In the next step, SmartPLS is used to perform 10-fold cross-validation, which provides mean absolute error (MAE) for endogenous and mediator constructs using linear and PLS-SEM models [73]. Their comparison is shown in Table 4, which indicates that most indicators exhibit less error for PLS-SEM_MAE compared to the linear model (LM_MAE). Moreover, the values of Q^2 >0 for all indicators show that the model has strong predictive power.

5.5. Necessary condition analysis (NCA)

NCA is a data analysis tool that was first devised by [74], making it possible to identify necessary conditions in given data sets. NCA generates a ceiling line on top of the given data [75]. The ceiling line represents the least number of independent variables needed to attain a

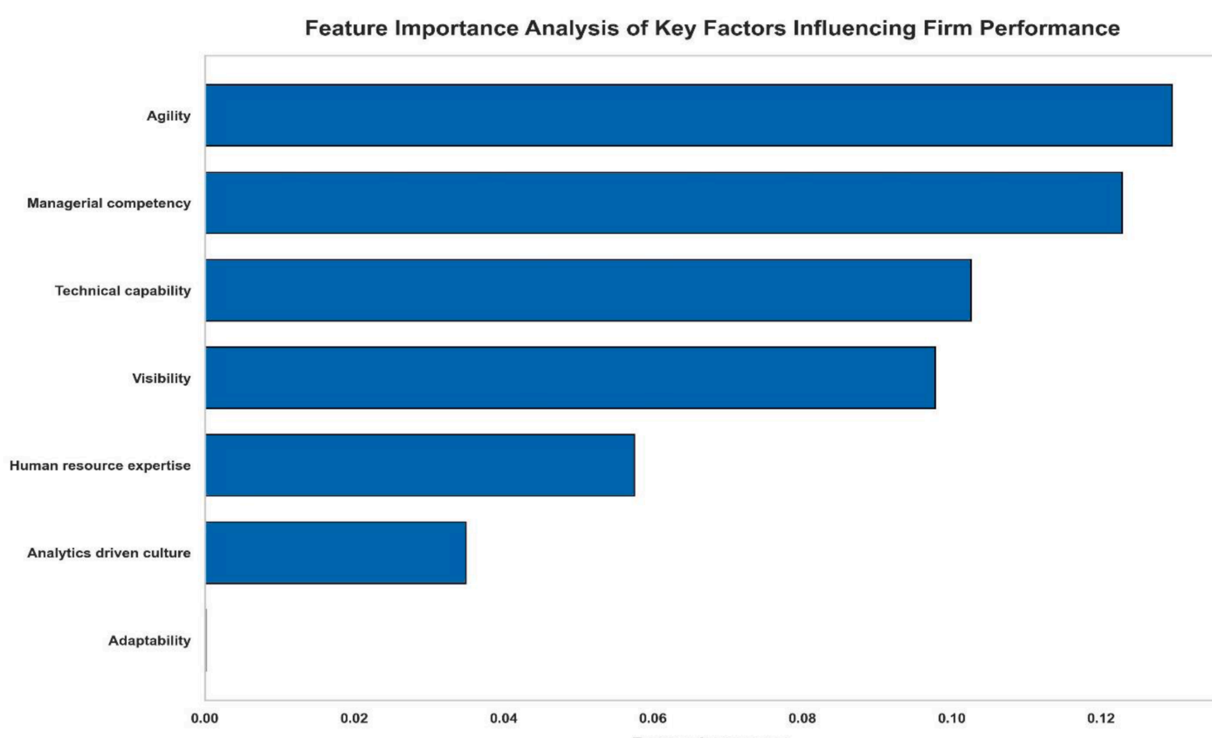

Fig. 3. Feature importance analysis using SVR.

Table 4
Results of PLSpredict for the assessment of predictive power.

	Q^2predict	PLS-SEM_MAE	LM_MAE	(PLS-SEM_MAE)-(LM_MAE)
Adap1	0.174	0.511	0.531	−0.02
Adap2	0.117	0.651	0.66	−0.009
Adap3	0.155	0.587	0.594	−0.007
Adap4	0.271	0.456	0.466	−0.01
Agil1	0.132	0.643	0.634	0.009
Agil2	0.174	0.58	0.582	−0.002
Agil3	0.131	0.571	0.568	0.003
Agil4	0.211	0.54	0.552	−0.012
Agil5	0.247	0.489	0.497	−0.008
Perform1	0.026	0.564	0.58	−0.016
Perform2	0.032	0.632	0.644	−0.012
Perform3	0.031	0.596	0.61	−0.014
Perform4	0.028	0.598	0.609	−0.011
Perform5	0.125	0.47	0.495	−0.025
Visi2	0.143	0.737	0.748	−0.011
Visi3	0.217	0.567	0.574	−0.007
Visi4	0.294	0.575	0.579	−0.004

given number of dependent variables. The ceiling line findings are tabulated in Table 5. The outcome is shown in the first column of the table, and any necessary conditions are shown in the following columns.

To get a comprehensive output, NCA is run on SmartPLS. The endogenous construct in the present research is firm performance, while exogenous constructs include AC and DC. First, partial regression results are analyzed. All values of the VIF were below 3.3, as shown in Table 1 and as mentioned in Section 5.2. Moreover, the value of R^2 for firm performance is 0.136. Results indicate that AC (effect size=0.144, $p = 0.000$) and DC (effect size=0.195, $p = 0.000$) are significantly necessary conditions for firm performance. Both variables exhibiting medium effect sizes based on the criteria outlined by [74]. Table 5 facilitates a detailed examination of each condition. For instance, attaining 80 % performance requires fulfilling two conditions: Analytics Capability (AC) must be at least 63.46 %, and Dynamic Capability (DC) must be no less than 77.64 %.

5.6. Robustness of model

5.6.1. Nonlinear effects

There may exist very complex relations between variables that do not follow a linear pattern. Instead of showing the linear relation, they can show a curvilinear line, exponential effects, or any other complex patterns that are essential to analyse to get a precise depiction of the results. The strategy to capture this non-linear relationship is the effort to provide a deep understanding of the variables, which will improve the explanatory capability of the model. Nonlinear models also capture the variances that linear models treat as random errors, so it is used to be more robust and reliable to analyse the data [76] developed a method to assess the nonlinearities in the data. The regression equation specification error test (RESET) is a technique that is used to evaluate the data [77]. To conduct RESET, the construct score developed by SmartPLS is used as input [78]. In the "R" language, a package named "lmtest" is used to run the RESET.

First step was to run the bootstrapping test in SmartPLS, and the results reveal that quadratic effects of analytics capability on firm performance (path coefficient= −0.022, p-value= 0.530) and dynamic capability (path coefficient= −0.017, p-value= 0.456) were found to be insignificant. Similarly, the quadratic effect of DC on performance is also not significant (path coefficient 0.083, p-value 0.073). Now, the combined effect of AC and DC on firm performance is evaluated through RESET, and no nonlinearities are found to be significant (RESET = 0.26469, p-value = 0.7676).

5.6.2. Endogeneity

Now, endogeneity is another problem that arises when predictors show a correlation with the error terms of output constructs, leading to parameter estimates that are not correct and providing conclusions that are misleading [79]. It is quite interesting that in this phenomenon, predictor explains the endogenous variable as well as its error terms [80]. To assess this problem, the technique used is called the Gaussian copula (GC) developed by [81]. GC is used by using SmartPLS, and findings of Table 6 indicate that problem of endogeneity is not significant. All possible GC combinations of the model are evaluated as shown, and nothing is found to be significant. These results conclude that this model is robust.

5.6.3. Unobserved heterogeneity

The third step to check the robustness of the model is to assess the unobserved heterogeneity. If there exist some subgroups in the data that show some different model estimates, then it is essential to consider them for the complete assessment of model. To handle this issue, [63] provided a methodology that uses the latent class technique. For this purpose, FIMIX-PLS is very useful as it produces a number of clusters that should be retained [82]. Before using this technique, first step was to compute the smallest sample size using G*Power" software. A sample size of 40 was calculated by the software to extract the total 10 segments with an 80 % power level and an effect size of 0.15. From 1 to 10 segments are run using FIMIX-PLS, which shows very interesting results as shown in Table 7.

The minimum values of AIC3 do not come into the same portion as those of BIC and CAIC, but an important factor is that minimum values of AIC4 and BIC fall in the same segment, i.e., second segment. The

Table 5
Results of NCA in percentage.

	Firm performance	Analytics capability	Dynamics capability
0.00 %	−1.933	0	0
10.00 %	−1.433	0	0
20.00 %	−0.933	0	0
30.00 %	−0.433	0	0
40.00 %	0.066	0.24	0
50.00 %	0.566	6.731	0
60.00 %	1.066	18.99	4.087
70.00 %	1.566	44.471	38.221
80.00 %	2.065	63.462	77.644
90.00 %	2.565	74.519	92.548
100.00 %	3.065	85.337	98.558

Table 6
Results of Gaussian copula.

Test	Constructs	Coefficient	P values
(Endogenous variable; DC)	AC -> DC	0.715	0.000
	AC-> Firm performance	0.185	0.003
	DC-> Firm performance	0.642	0.008
	GC (DC) -> Firm performance	**−0.445**	**0.069**
(Endogenous variable; AC)	AC -> DC	27.29	0.000
	AC -> Firm performance	0.335	0.738
	DC -> Firm performance	3.102	0.002
	GC (AC) -> Firm performance	**1.345**	**0.179**
(Endogenous variable; AC)	AC -> DC	0.627	0.000
	AC -> Firm performance	0.189	0.003
	DC -> Firm performance	0.209	0.002
	GC (AC) -> DC	**0.092**	**0.501**
(Endogenous variables; AC, DC)	AC -> DC	0.715	0.000
	AC -> Firm performance	−0.324	0.129
	DC -> Firm performance	0.911	0.001
	GC (DC) -> Firm performance	**0.728**	**0.067**
	GC (AC) -> Firm performance	**0.535**	**0.054**

Table 7
Values of fit indices for 10 segment solution.

Criteria	1	2	3	4	5	6	7	8	9	10
AIC (Akaike's information criterion)	4116	3995	3951	3907	3891	3854	3839	3836	3766	**3739**
AIC3 (modified with Factor 3)	4139	4042	4022	4002	4010	3997	4006	4027	3981	**3978**
AIC4 (modified with Factor 4)	4162	**4089**	4093	4097	4129	4140	4173	4218	4196	4217
BIC (Bayesian information criterion)	4209	**4185**	4237	4290	4370	4430	4512	4606	4633	4702
CAIC (consistent AIC)	**4232**	4232	4308	4385	4489	4573	4679	4797	4848	4941
HQ (Hannan-Quinn criterion)	4153	4070	4064	**4059**	4080	4082	4105	4141	4109	4120
MDL5 (minimum description length with factor 5)	**4764**	5318	5950	6582	7241	7880	8540	9214	9819	10,467
LnL (LogLikelihood)	**−2035**	−1951	−1904	−1859	−1826	−1784	−1752	−1727	−1668	−1630
EN (normed entropy statistic)	0.000	0.449	0.530	0.607	0.670	0.767	0.742	0.762	0.780	0.806
NFI (non-fuzzy index)	0.000	0.498	0.524	0.569	0.614	0.700	0.660	0.687	0.681	0.719
NEC (normalized entropy criterion)	0.000	229	195.4	163.4	137.1	97.0	107.4	98.9	91.7	80.9

performance of these two parameters is also regarded as good in FIMIX-PLS. So, it can be concluded that there exists heterogeneity with two segments (Sample 1 = 51.5 %, Sample 2 = 48.5 %) solution [82,83]. In the next stage, a comparison is conducted for unobserved heterogeneity with observed heterogeneity on the basis of organization's size. Out of 416 collected responses, 218, which constitute 52.4 % of the total sample, are from large organizations (having > 250 employees), and 198 responses, which constitute 47.6 % of the total sample, are from medium-sized organizations (having <250 employees). All the segments are validated through bootstrapping, and results are provided in Table 8.

All the results of reliability and validity fulfil the criteria for all the clusters. Model is successfully validated for a complete sample, but segments 1 and 2 show differences in the validation of AC and DC on firm performance. For further understanding, model is run for bootstrapping for large and medium firms separately, which shows some interesting facts, as all hypotheses are validated for medium-sized firms, but one hypothesis is not validated for large organizations, i.e., the effect of DC on firm performance. It can be inferred that medium-sized organizations are more flexible than larger ones, which are more stable and rigid. So, medium-sized firms can spend more resources on developing and adapting the DC quickly and can leverage their benefits. DC in medium-sized firms can provide more benefits due to their less complex structure and easy adaptation, while large firms are more focused on maintaining their market share, and their focus is more on scale efficiency. Similarly, large organizations have a very robust innovation system, and they are less inclined to take risks, which constrains their abilities to adapt to the dynamic capabilities while medium-size firms are more risk tolerant and their structure and culture support innovation.

6. Discussion and implications

The findings should be interpreted considering the DCV, which considers the sensing, seizing, and reconfiguring abilities as the micro foundations of organizational adaptability. The results indicate that AC serves as a sensing mechanism that can process large and unstructured datasets to sense market situations and trends. DC, in turn, represents the seizing and reconfiguring dimensions, whereby organizations translate sensed signals into actual resource realignments. This interpretation highlights that AC is not just a technical tool but a theoretical precursor that triggers the mechanisms outlined in DCV. Thus, the theoretical contribution is a stronger linkage between DCV's foundational logic and the operational realities of FMCG supply chains.

The results of the current study about role of AC in DC and firm performance are also congruent with prior empirical studies in supply chain analytics [84,85]. For example [86] found that big data analytics capabilities have a strong positive influence on both SC agility and overall firm performance. Similarly, [87] also confirmed about positive impact of big data on firm performance through agility as a mediator. Also [37] examined the effect of big data on firm performance, which confirms results of the current study. Such consistency supports the theoretical proposition that analytics capabilities are a key driver of responsiveness and competitive advantage in dynamic environments. However, unlike previous studies, this research focuses on the FMCG sector in an emerging economy. This focus brings to light new insights into how analytics capabilities can be harnessed under resource constraints, short product life cycles, and volatile demand, which are typical of the FMCG environment in markets like Pakistan. Therefore, current research adds contextual knowledge and facilitates the broader generalizability of the analytics-dynamic capability-performance framework. The study not only contributes to the theoretical knowledge to understand DCV but also provides insights to the managers and practitioners working in FMCG sector.

6.1. *Theoretical implications*

This research improves the understanding of how AC is a very important antecedent to developing the DC, which consists of organizational visibility, agility, and adaptability. Analytics can improve performance by streamlining the process, identifying the wastages in critical areas, analysing the current market trends, and enhancing operational performance. With analytics, firms can track the performance of their product in different regions and can take action through better resource allocation. For example, AC can provide insights about the products underperforming in different demographics and can guide managers about their corrective actions. The research uses DCV, which is a foundational framework in the field of SC, and it encourages the firms to combine, create, and restructure all the internal and external capabilities so that these firms can face the challenges of rapidly changing market demands. This research supports the DCV by

Table 8
Results of heterogeneity.

	Complete sample		First Segment		Second Segment		Large firms		Medium firms	
	Coeff	P Value	Coeff	P Value	Coeff	P Value	Coeff	P Value	Coeff	P Value
AC-> DC	0.715	0.000	0.505	0.000	0.945	0.000	0.712	0.000	0.710	0.000
AC -> Firm performance	0.189	0.003	0.217	0.003	0.281	0.149	0.163	0.045	0.215	0.025
DC -> Firm performance	0.209	0.002	0.092	0.034	0.212	0.281	0.138	0.121	0.269	0.005
Validity and Reliability										
Cronbach's Alpha										
AVE										

empirically validating the positive mediating role of DC with a focus on consumer goods industry, in which agility and responsiveness are considered very critical factors.

If any of the firms develops a strong foundation in analytics, it will have an advantage in sensing the changes in customer preferences quickly, and it can seize the opportunities and reconfigure its resources accordingly. In this way, it can improve its market share, profitability, and customer loyalty. From the perspective of DC, this concept is completely aligned with the higher-order DC as it reflects the ability of an organization to not only adjust the daily operations but also make it capable of adapting to changes at the strategic level in case of any sudden disruption in SCs [88,89]. This study also adds to literature of DCV by introducing the turbulent nature of the FMCG sector. FMCG markets are marked by high volatility, fast-changing consumer tastes, and heavy competitive pressures, and hence pose the most suitable setting for validating the theoretical hypotheses of DC against high uncertainty. Based on contingency theory [90], this research highlights that analytics and DC need to be considered in context, whereby their impact on improving firm performance depends significantly on a volatile environment. Thus, this research adds to theoretical insight by empirically illustrating that the interrelationship between AC, DC, and performance is dependent on the industry-based context and market forces prevalent in FMCG. The study also strengthens the sustainability perspective by pointing out that DC, together with analytics, increases the ability of firms not only to respond quickly to volatility of market but also to strategically respond to sustainability challenges by optimizing their usage of resources, reducing waste, and lowering environmental footprints [91]. This research, therefore, gives theoretical explanations on how strategic alignment of analytics and dynamic capabilities directly assists businesses in obtaining sustainable development objectives, especially in industry segments such as FMCG, where both environmental and social obligations continue to be more dominant. Thus, this research contributes by explaining that analytics not only improves real-time responsiveness but also is a key factor in improving operational flexibility and strategic shifts.

6.2. Managerial implications

In the rapidly growing consumer goods industry, firms need to be responsive to consumer demands. This research highlights the managerial implications of AC to improve DC and ultimately firm performance. Due to rapidly changing consumer demands, limited resource availability, and regulatory pressure, managers should give priority to integrating the AC into their decision-making process. The managers in FMCG can anticipate and react to change in a better way by collecting and analysing the data and deriving insights from it, which not only increases the agility but also resilience of the firms. AC can improve the organization's visibility, which can help the SC managers to identify consumers' demands, contemporary trends, and expected risks, making it easier for them to take preventive measures during production, marketing, and distribution. This insight is very important for the consumer goods industry because managers in this industry are facing many challenges, including unstable markets & SCs, emerging sustainability issues, and fast-paced product innovation. Managers can use analytics to analyse real-time SC data, find the bottlenecks in the operations, and develop strategies for logistics or sourcing accordingly. This agility and adaptability, due to AC, emphasize that a fully developed analytical foundation is not only supportive but foundational to DC in a rapidly changing consumer market.

In a very competitive sector like consumer goods, performance metrics such as customer satisfaction, operational efficiency, and responsiveness to market are highly dependent on data-driven decision-making system. AC is very useful for managers, specifically in areas such as quality control, forecasting of demand, and inventory management. One example is that by analysing the purchasing patterns of consumers, managers can improve their forecasting about the fluctuation in demand, thus developing their production scheduling accordingly and ultimately minimising waste and optimising the inventory. This, in turn, improves the metric of performance that is cost-saving and increases the profit margins. Moreover, the relationship between DC and firm performance emphasizes the role of flexibility and adaptability to gain a sustained competitive edge. For this research, DC is taken as a mediator between AC and performance, and it validates that full advantages of AC can be obtained only if firms are capable of using the insights dynamically. This study suggests that SC managers should not only invest in developing a data-based infrastructure, but this infrastructure and culture should also be flexible enough to adapt to the rapid changes in the environment and continuous improvement. Managerially, analytics-enabled DC not only improves competitive performance but also helps managers in achieving sustainable development. Through the use of analytics to improve demand forecasting, optimize inventory, minimize waste, and increase supply chain transparency, managers can dramatically decrease the environmental footprint of their companies. DC also allows managers to adjust organizational practices quickly to address changing sustainability regulations, stakeholder demands, and environmental issues. Hence, investment in analytics capability and development of dynamic capabilities offers managers within the FMCG industry a strategic route to achieving operational excellence and sustainability objectives concurrently.

But the most important thing is that developing analytics capability in any firm goes beyond building the infrastructure and technological investments. It needs a data-driven culture, where everyone values decisions based on data. Managers are required to promote a culture of data literacy and experimentation, where employees at all levels should be fully trained to handle and interpret data, ensuring that all decision-making is informed by real-time information. Bringing about a cultural shift is always very challenging, especially in traditional organizations, where decisions are often based on experience or intuition. However, the findings of this study suggest that firms which prioritize the adaptation of a data-based approach will be in a better position to shift themself according to prevailing changes. So, managers should encourage the employees to consider the generated data as a strategic asset of firms. Firms must employ advanced networking technologies to achieve dynamic resource reconfiguration, establish a digital network, and facilitate communication across firm boundaries. In addition, companies should cultivate strong ties with their SC partners to enhance sharing of information. Managers can exchange information regarding the diversity of customer demand and subsequently collaborate with their suppliers to formulate procurement and production plans. Integration of both AC and DC in the infrastructure and culture of any organization provides a new pathway to improve performance and enable the firm to navigate uncertainty and explore new opportunities.

7. Conclusion

The purpose of this research was to emphasize the important role of AC in improving the DC and performance of the firm in FMCG sector. The findings validate that AC has a positive impact on DC and firm performance, as well as DC not only has a direct effect on performance but also plays a complementary partial mediation between AC and performance. DC, which consists of three constructs, visibility, agility, and adaptability, is important to exploit the AC in the rapidly evolving sectors where responsiveness is important to sustain the competitive edge. Using these attributes, organizations can be responsive to rapidly changing markets & consumer preferences and operational problems with better accuracy, which may position the AC as a key input parameter of strategic adaptability.

While the research provides very strong evidence about the benefits of AC and DC for the performance of firms in FMCG sector, there are some limitations to this research. The strength of the effect of AC and DC on performance is dependent on many factors such as legal obligations, tech infrastructure, and market situations. An example is that the AC of a firm can be constrained due to highly regulated environments, and hence full benefits of DC cannot be achieved. Another problem is that firms that have limited resources, especially small and medium-sized enterprises, may face challenges in the integration of analytics across SC because it requires strategic partnerships as well as investment in training the personnel. Another major limitation of the research is that it only focuses on FMCG, which is very volatile and faces rapid market fluctuations, but the findings of this study cannot be generalized to other sectors such as heavy industries, where all the market dynamics are different and the relationship of AC, DC, and performance can be observed in a different context. The DC for this study is measured in a structured manner through visibility, agility, and adaptability; however, there may be other constructs that are being overlooked in this research. Moreover, no external factors are considered, including the barriers to adoption of technology, cultural issues, and regulatory requirements, which can limit the effectiveness of AC. Considering all these variables can improve the robustness of the model and provide a better understanding and deep insights into the effects of AC and DC in different situations. Additionally, there are some methodological limitations. Firstly, cross-sectional survey data restrict causal inference. Second, the study is based on perceptual measures, which can cause the common method bias even with procedural corrections like anonymity and use of marker variables. Thirdly, while the SVR model enhances prediction, it is not as interpretable as SEM.

Based on these findings, future research can explore different approaches. Application of this model to different industries can explore the observed relationship of these variables across different sectors with different levels of technical competency and different market dynamics. Although the R^2 value of dynamic capability is reasonable, the R^2 value of firm performance (0.136) is quite limited, suggesting that there are other significant factors contributing to performance that have not been measured in this model. Future studies can include more explanatory variables like innovation capability, digital maturity, supply chain integration, or organizational culture to enhance the predictive ability of the model and offer a richer explanation of the drivers of firm performance. The effect of different types of analytics (predictive vs. Prescriptive) can be explored on DC and firm performance. Moreover, assessment of specific dynamics of SC, such as its complexity and market unpredictability, should be considered for mediating or moderating effects. Observing these factors can provide deeper insight into achieving the maximum outcome of a data-driven system, as well as dynamic capability. To address the methodological limitations, longitudinal data can be used to establish causal relationships and analyse temporal dynamics. The objective performance can be integrated with the operational and financial records. There is continuous advancement in technologies, so it can be further explored how machine learning and artificial intelligence can be integrated into the framework to provide improved performance in data-driven industries. The findings of this research have important implications for the industry stakeholders and policymakers as they can provide incentives or subsidies to FMCGs, especially small and medium-sized, to acquire advanced analytics techniques to gain overall competitiveness.

CRediT authorship contribution statement

M. Adeel Munir: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Muhammad Mujtaba Abbas:** Writing – review & editing, Visualization, Methodology, Conceptualization. **Adnan Qamar:** Writing – review & editing, Software, Resources, Methodology. **Muhammad Farooq:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Data curation. **Viktorija Cohen:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

No conflict of interest.

Data availability

Data will be made available on request.

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